Housing and Inequality: Visualizing Barrio Transformation from Unrestrained Development

GOLDER KAMUZORA
JACOB LOGAS
NORA MENCINGER
MAJID AHMADI
ZEYNAB BAHRAMI BIDONI
BREANNA LEE

Fig. 1. A wall divides a gated community from a shantytown in outer Buenos Aires. Natacha Pisarenko / AP

Authors' addresses: Golder Kamuzora, golder.kamu@gatech.edu; Jacob Logas, logasja@gatech.edu; Nora Mencinger, nmencinger3@gatech.edu; Majid Ahmadi, majid.ahmadi@gatech.edu; Zeynab Bahrami Bidoni, zbahrami@gatech.edu; Breanna Lee, breanna.lee@emory.edu.

1 INTRODUCTION

1.1 Motivation

The Buenos Aires (Baires) economy is in turmoil with the peso at record lows (see Fig 2), wealth inequality expanding, and housing prices increasing due to rapid gentrification [25]. Researchers hypothesize neighborhoods quickly transform to attract wealthier citizens because Baires has few public housing policies and lightly regulated private developers [10]. This behaviour is seen in the United States as well, with the largest cities quickly developing with little regard for the poor.

We will study the effects these events have on Baires's social and economic makeup to improve awareness of issues which arise from wealth inequality and lax metro development regulations. Our analysis could encourage local governments to slow private development and increase public housing investment.

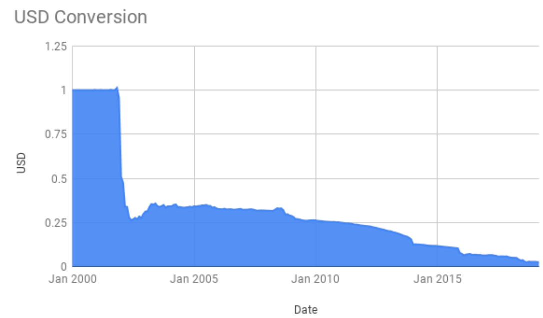


Fig. 2. Conversion: Argentinian Peso to USD (2000-2019) [4]

1.2 Problem Definition

We will characterize Baires's barrios (neighborhoods) and motivating factors for purchasers each year by analyzing housing trends using statistical analysis and machine learning techniques. From the analysis, we will identify important structural (eg. types of home, number of rooms, etc) and locational (eg. access to transportation, crime rate, etc) characteristics.

1.3 Innovations

Existing housing research is more history driven than data driven. Baires visualizations provide insights into travel infrastructure and poverty [5, 7], but do not use the data to form any conclusions. Thus, we will contribute the following:

- Data driven analysis of housing purchaser motivations in Baires
- Baires barrio characterization with price estimation function
- Informative and interactive visualization

2 RELATED WORK

2.1 Policy Effects

Di Virgilio studied effects of the Federal Housing Plan in Argentina after the 2001 crisis. The author found the policies did not achieve their objective of mitigating deficits caused by lack of available land [16]. Virgilio and Rodriguez similarly studied resistance to state-promoted gentrification, which displaces low-income citizens [23]. This study gives context to the broader issues of Baires citizens and motivates our analysis.

Blanco and Apaolaza analyzed socioeconomic disparity in public transportation for Baires. This provides insight into usage patterns but does not consider housing or the analysis of socioeconomic positioning, leaving room for development [9].

Several works guide our analytics by providing historical, economic and social background. Thomas et al. reviewed Argentinian economics after the 2001 financial crisis which led to political and economic instability that resulted in another crisis in 2014 [24]. Borsdorf et al. illustrated the difference housing policy makes in metro areas by comparing Baires with Santiago del Chile. They found wealth inequality in Baires is shaping the city so gentrified areas grow at the expense of poorer citizens [10]. Lehr noted residential isolation of poorer citizens reduces their upward social ability and aggravates divisions between classes [20]. Additionally, Agarwal et al. found mortgage borrowers defaulted and became further disadvantaged after the government halted foreclosures and issued a policy to protect debtors in the 2001 crisis[6].

Xu et al. investigated how monetary policies impact real estate price growth in China. They found the policies and bullish markets are driving forces behind price growth [26]. This work provides insight on how policies shape housing markets in other countries.

2.2 Modeling Housing with Hedonic Pricing

Baldominos et. al analyzed real estate data using K-Nearest Neighbors and Support Vector Machines with some success. We will use more sophisticated techniques for the Baires housing market as well as replace mean error with AUROC as our performance measure [8].

Crowd-sourced data from real-estate websites have been used to model markets. Nadai and Lepri developed a predictive model, based on XGBoost, for eight Italian cities using neighborhood locational characteristics specifically security, living conditions, and cultural capital [14]. Previously, they used mobile phone data and a safety score to find connections between the levels of activity and safety perception for neighborhoods in two Italian cities [15]. Li similarly created economic models of communities in Shanghai [21].

Researchers also investigated factors which effect amenity values. Fu et al. created an accurate model for Beijing real-estate pricing by including geographic factors like proximity to public transit [17]. Similarly, Cho et al. developed a model for urban forest landscapes across a metropolitan county [13]. Cheshire et al. investigated how locational features factor into price [12].

Guerra et al. revealed that availability of public transit is a major factor for which areas are gentrified first and contributes to an inverse relationship between the cost of housing and normal transportation costs [18]. This work provides a potential framework for relationship analysis between geography, household location, and expenditures.

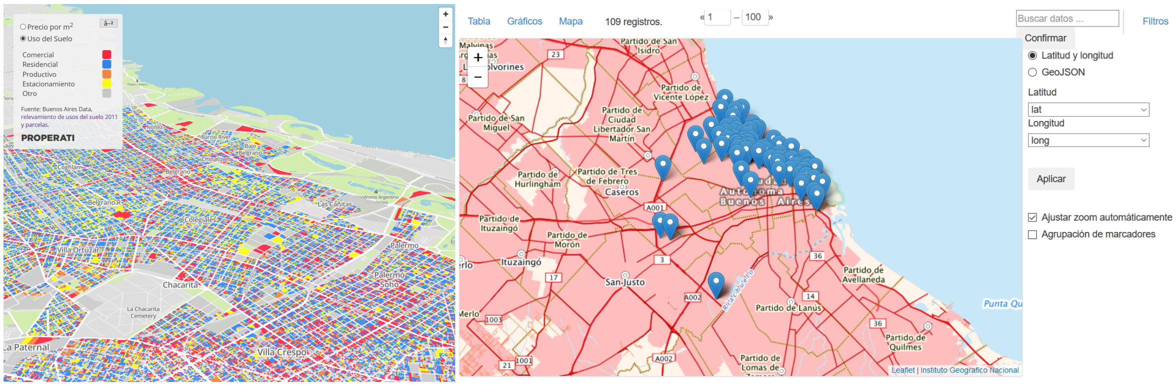
Finally, Camacho et al. advocate a dynamic factor model to provide alternative measures of Argentine GDP since 2007. This uses indirect information from economic indicators [11].

3 METHODS

3.1 Intuition

Baires lacks data-driven research on its housing policies. We used public data of public goods and income from Baires's transparency portal [1] and Argentina's 2010 Census data to characterize the barrios. These were analyzed for insight into the barrios of Baires and how they are changing over time.

Despite the large quantity of available data from the Baires government, Properati has only analyzed their own data. As Properati data is user generated, accurate reporting of a property's characteristics is not guaranteed. Conversely, the Baires government only has simple graphics of the data with no analysis. By combining these datasets and creating informative visualizations, we are able to provide a clearer picture of the Baires housing market.



(a) Properati housing visualization [2]

(b) City of Buenos Aires data visualization [1]

Fig. 3. Current approaches to visualization of Baires data.

Figure 3a shows Properati's visualization of barrio price data. By using 3D modelling, it runs slowly and uses a large amount of computer resources. In addition, this visualization provides little insight into the communities. This heatmap is superimposed over housing blocks rather than over barrios which results in small points lacking a clear pattern.

Figure 3b illustrates the government's approach to visualizing their data. It is simplistic: a map of Baires with tagged points of interest. The visualization is useful for identifying the breadth of data and specific locations of points of interest, but has no associated analysis.

Combining the datasets provides more context and by presenting the data at a higher level, we can improve upon both visualizations. Reducing the granularity to barrios and using efficient computations also improves the runtime and reduces the use of computer resources.

3.2 Data Collection and Cleaning

The following datasets were collected:

- Properati's listings (rent and sale) [3] between January 2015 and March 2018
- Baires's officially recorded property sales between 2001 and 2018
- Argentina's 2010 census data
- Polygons of Baires barrios
- Locations of public goods (transit, hospital and medical centers, etc.) from Baires' government

NUNEZ NU?ÆEZ NU?EZ	NUÑEZ
VILLA GRAL. MITRE VILLA GRAL. MITR VILLA GRAL MITRE	VILLA GENERAL MITRE

Table 1. Example of entry or encoding errors accounted for when partitioning into barrio.

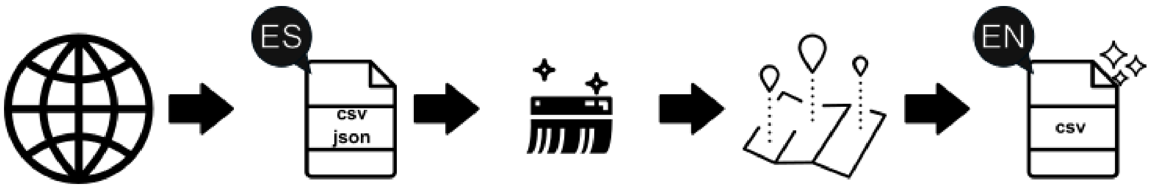


Fig. 5. Data preparation pipeline.

Type	Description	Row Count
Rent	Raw Properati Rental Data	265181
	Properati listings within the Autonomous City of Buenos Aires	65574
Purchase	Raw Properati Purchase Data	1871732
	Properati listings within the Autonomous City of Buenos Aires	464869
	Unique Properati listings within the Autonomous City of Buenos Aires	116425

Table 2. Results of data cleaning operations.

Properati's listings dataset was collected from Google's BigQuery software while all other datasets were freely downloadable as either JSON or CSV files. All the datasets had geospatial information, either longitude and latitude points or sets of longitudes and latitudes that form a polygon. OpenRefine filtered Properati listings and merged the public goods files for further processing.

The Pandas Python data manipulation package was the predominant cleaning tool. As the raw information is in Spanish, special characters and formatting errors were cleaned first (see Table 1) and then duplicate listings were deleted. It was discovered Baires, the city, shares the name with the Buenos Aires Province, a community Properati also services. Therefore, the location data was filtered to only keep points inside the Baires city limits. Figure 4 illustrates the entirety of the Properati listings from Baires province over the city polygon (blue).

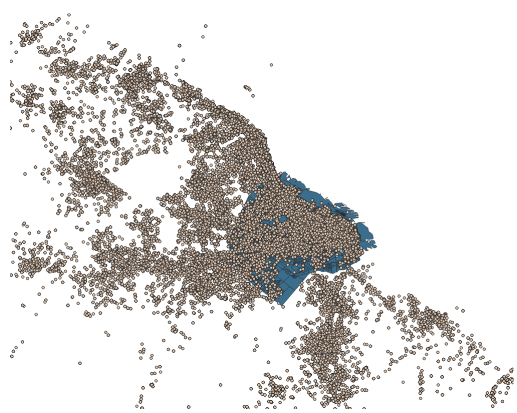


Fig. 4. Full data of Properati in relation to Baires.

We performed spatial joins between Properati's point data and the Census's barrio polygons using Python's GeoPandas package. The Nearest Neighbor Join algorithm matched each Properati listing with the nearest government property values record. Although the data was reduced by 75% (Table 2), we were able to concentrate our analysis on the city itself, which had a wealth of supplemental data.

4 BARRIO ANALYSIS

Price gap prediction and feature selection: Feature selection is normally used to reduce the feature set before training a model with minimal accuracy loss. This technique provides similar results to Principal Component Analysis, Independent Component Analysis, and Latent Derelict Analysis; however, feature selection uses a heuristic to determine an importance score per feature, given a target variable. In our approach, we determined mutual information regression (MIR) with entropy was the most effective method [19]. Using MIR, we performed feature importance analysis of public goods and census data over price for insight into seller motivation.

Mislabelled barrios: Here, we investigate the *Buckhead effect*, a reference to the Atlanta neighborhood of Buckhead. This is the phenomenon of housing listings near affluent neighborhoods incorrectly listing their location as within the neighborhood to boost visibility or price. To investigate this, we compared the self-reported barrio with the actual barrio based on provided geographic coordinates; the mislabelled listings were then further analyzed. Correlation between mislabelling rates and census features for each barrio was calculated to uncover trends.

Price Gap Analysis: Using the join between government property values and Properati listing values, differences between the listed and final purchase price were analyzed. The official property price dataset was filtered to listings linked to properties sold between 2015 and 2018. The difference was used as the target variable in feature selection with the same features as before to determine what leads to a discrepancy between the listed price and final selling price.

5 VISUALIZATION

Our results are visualized with a web application using *JavaScript* visualization packages like D3 and the web frameworks *Vue.js* and *Bottle*.

5.1 Housing Overview

The first state of the application is a heatmap of Baires, divided into its barrios (Fig. 6). Two options are "Purchase Price" and "Rent", which calculate statistics using either Properati sale data or rent data. Available statistics are:

- Average (6a)
- Maximum (6c)
- Minimum (6b)
- Standard Deviation (6d)
- Proportion above 90th Percentile (6e)
- Proportion below 10th Percentile (6f)

The first four statistics are calculated as normal, then displayed as a heatmap overlaid on the barrios. Dark blue represents the highest value in the range (even for the minimum plot). For the last two statistics, prices for all Baires are considered to determine those greater than the 90th percentile and less than the 10th percentile. The heatmap then shows dark blue for the greatest percentage of homes either above the 90th percentile or below the 10th.

Next to the heatmap, circles show percentages of home ownership, rentals, and uninhabited properties from the census data. Initially these percentages are for the whole of Baires (Figure 7) but as barrios are explored they become more specific.

(a) Average (b) Minimum

(c) Maximum (d) Standard Deviation

(e) % > 90th Percentile (f) % < 10th Percentile

Fig. 6. Heatmaps of Purchase Price and Percentage Circles

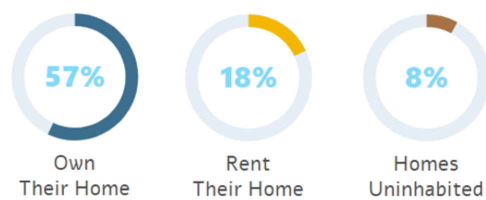


Fig. 7. Ownership, Renting, and Uninhabited Percentages for Baires [22]

5.2 Barrio View

When a barrio is clicked in the heatmap, a closer view is displayed along with the name and a short description. The census percentages dynamically change to show the percentage of home owners, renters, and uninhabited homes for the selected barrio as well as counts of cultural landmarks, health providers, social care centers, and sports amenities (Table 3).

Once a barrio is selected, a second block is visible at the bottom of the application with navigable tabs.

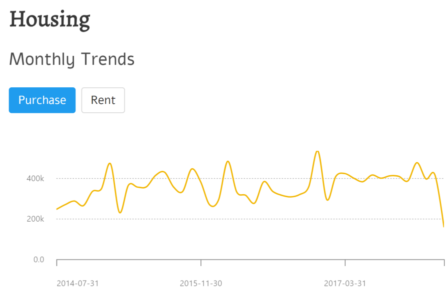
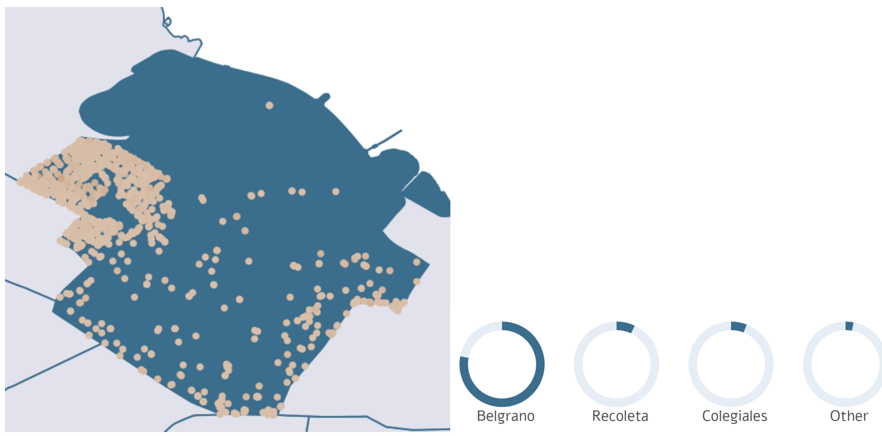


Fig. 8. Purchase Prices in Palermo by Month



(a) Mislabeled Listings (b) Percent mislabeled for neighboring barrios

Fig. 9. Mislabeling in Palermo

5.3 Overview Tab

Overview displays graphs of purchase and rental prices in the selected barrio over time (Figure ??). These prices again come from Properati's listings for sales and rentals.

To the right of this graph are some of the barrio's basic statistics in USD: Maximum Price, Average Price, and Standard Deviation.

5.4 Analysis Tab

Analysis contains two parts described below.

Mutual Information Regression: At the top are short descriptions of the important features by region of Baires, results of our MIR feature analysis. Below, Mutual Information Gain scores for the selected barrio are displayed between 2015 and 2018 for year to year comparison. Alphabetical feature ordering was implemented to facilitate comparisons between years and barrios.

Buckhead Effect: To visualize the Buckhead Effect, we mapped the selected barrio with points for each of the homes mislabeled as in another barrio. We also included circles to show occurrences of common mislabels. Mislabels occurring less than 3% of the time were grouped into Other. For example, Figure 9 shows Palermo's mislabeled homes (9a) and common mislabels (9b).

Category	**Description**
Cultural Landmarks	Museums, libraries, cultural centers.
Health Providers	Encompasses hospitals, pharmacies, community health centers, and medical centers
Social Care Facilities	Encompasses day cares, social orgs, women's shelters, elder care facilities, after-school clubs, etc.
Sports Amenities	Sports clubs, sports centers, skate parks, and football clubs

Table 3. Points of interest category descriptions

6 EXPERIMENTS AND EVALUATION

6.1 Wealth Distribution from Housing Listings

We performed the following experiments to test our hypotheses of wealth inequality in Baires.

Statistical Analysis: We characterized the barrios using the methods described above. Though the average listing price did not reveal much, when coloring barrios based on the proportion of listings above 90^{th} percentile and below 10^{th} percentile, a clear pattern emerges (Figure 6e & 6f). Coastal regions are shown to be wealthy with southern inland listings shown to be poor. Additionally, up-and-coming barrios with rapid development are apparent in the standard deviation heatmap, due to the prices changing rapidly each year (Figure 6d).

Price gap: We hypothesized sellers in wealthier barrios have greater motivation to advertise higher prices for their properties. We used Tableau to plot purchase listings with identified price gaps on Baires's map based on their coordinates. Figure 10 shows most of those homes are located in the northeast side of Baires, the more affluent region. From our analysis we made concluded affluent barrios in Northeast Baires have larger gaps than South Baires. Moreover, the gap is higher for medium to low priced listings and stays consistent between 2015 and 2018.

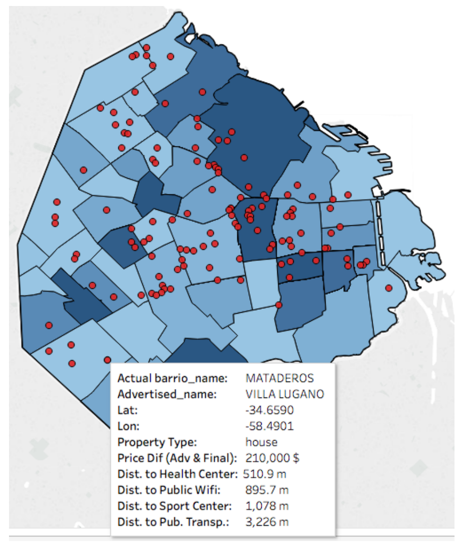


Fig. 10. Plotting the homes under consideration for price gap analysis.

6.2 Feature Importance

To determine the influential features in predicting the price gap and the barrio-level listed home price, we experimented with several feature-selection algorithms. We tested mRMR and linear regression with backward elimination (LRBE); however, the problem was time-complexity. For example, LRBE operates in $O(n^2)$, which is inefficient for high-dimensional data. A more efficient option is Mutual Information Regression (MIR) which has been shown to effectively compute error residuals for high-dimensional data. We computed MIR per barrio and for each of the years between 2015 and 2018.

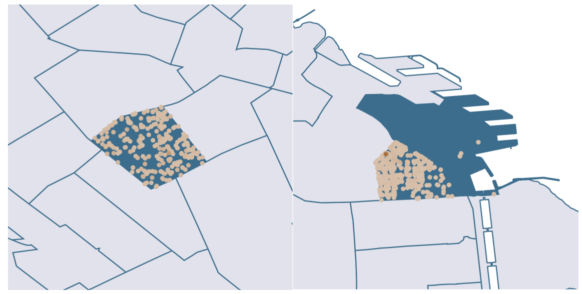
Feature selection analysis provided a basis to characterize Baires regions. Northern barrios have prices affected by education, health, and sports facilities at similar importance levels. Southern barrios, often poor or residential, lend more imporance to public Wi-Fi and health centers when determining price. Western Baires produced higher census education percentages despite schools and universities predominantly positioned in the East. Public transportation was found to be the most important feature across observed time in all regions of Baires.

6.3 Barrio Misclassification

6.3.1 Overall. In our analysis of barrio misclassification we found smaller, poorer neighborhoods misclassify more often and more evenly rather than misclassifications clustering on the edges.

Figure 11a shows Villa Santa Rita, a low-income barrio often confused with Villa Del Parque. Here, we see barrio listings misclassify well into the center of the neighborhood. From this, and other similar barrios, we conclude that poorer barrios are more likely to misclassify beyond what can be considered an accident.

On the other hand, Figure 11b illustrates an affluent barrio with a large cluster of misclassified listings. Retiro, although being affluent in its own right, neighbors a more historic neighborhood and in our analysis we saw a majority of misclassifications were into this historic neighborhood. A similar effect can be viewed in Figure 9, in which Palermo neighbors a historic neighborhood and is often misclassified into it.



(a) Villa Santa Rita (b) Retiro

Fig. 11. Two barrios misclassified differently.

6.3.2 Correlation. As seen in Figure 13, there is a negative correlation between educated population percentage and uninhabited properties. There is a highest price percentage proportion of -33% amongst the barrio, meaning high rates of education percentage, "price per m^2", and barrio's uninhabited rate tend to yield low rates of mislabeling.

Percentage of highest price per:

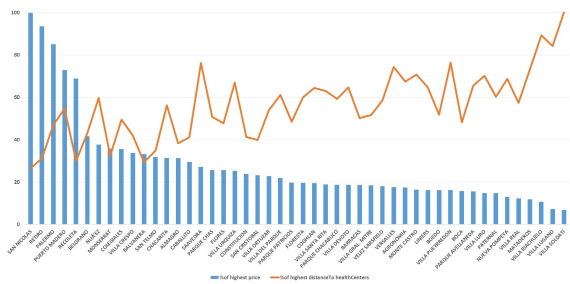
$$\frac{average\ price\ per\ m^2\ for\ a\ barrio}{highest\ average\ price\ per\ m^2\ between\ all\ barrios} * 100$$

We also observed features of "Computer Percent" and "Education Percent" have high positive correlation with a value of 85%. Therefore, when a barrio has a higher education level, we expect a higher rate of computer usage.

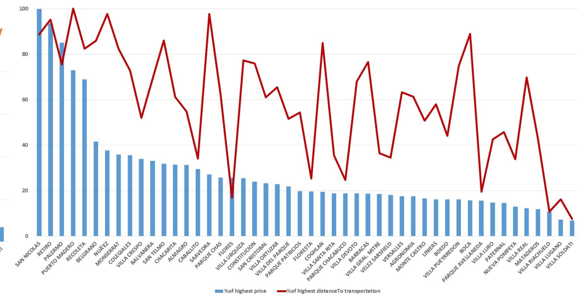
Figure 12 summarizes the correlations found between sale prices and the census and locational features. Figure 12c illustrates a positive correlation between computer ownership, education, and the barrio's percentage of highest price. Education and highest price is 75% correlated and computer ownership and highest price correlation is 47%. Health care center distance and price are inversely correlated at -61% (Figure 12a), meaning high price listings tend to be located close to health care. Finally, Figure 12b shows there is 55% positive correlation between distance to public transportation and barrio percentage of highest price. Meaning lower price properties tend to be closer to public transportation.

6.4 Usability and Impact Survey

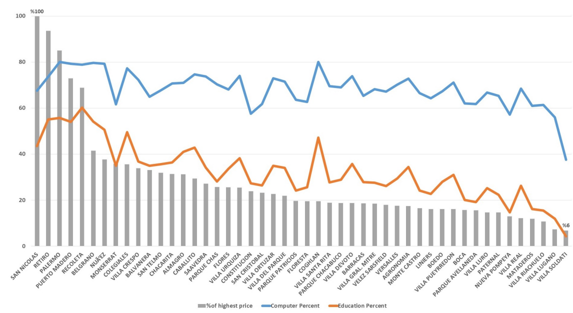
Within the application, we included a link to a survey to be taken after using the website. By using this survey we are able to collect data on how well our application conveyed information and how intuitive the design was. The results of the multiple choice questions in the survey and the questions themselves are summarized in Table 4. Overall the results show that this approach was moderately effective in relaying information about the Baires community. A final, short answer question aimed to see if the users were aware of what we were attempting to convey. In these answers we see that most users saw the correlations between census, locational, and housing data and how that is meant to relay information about Baires' economy.



(a) Distance to health care



(b) Distance to public transportation



(c) Education and Computer Ownership

Fig. 12. Top correlations between price and the census and locational features

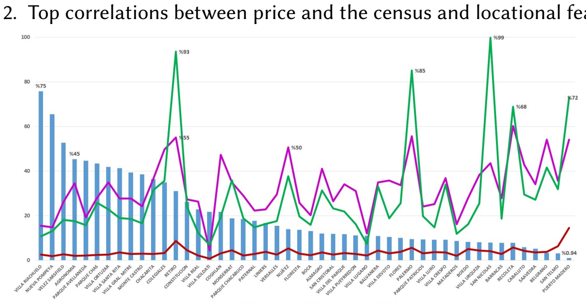


Fig. 13. Correlation of top three most significant features on mislabeling over each barrio.

7 CONCLUSIONS AND DISCUSSION

Based on the above visualizations and analyses, we were able to show that Baires' unrestrained development between 2015 and 2018 is reflected in the barrios' inequalities. We were able to use correlation and feature selection to show how housing prices in different barrios are affected by locational and economic features and how this is also mirrored in the city's recorded purchase records.

Our web application was able to communicate our analyses and conclusions to users, however, there was still a wealth of information that was not communicated during this project and can serve as further work for researchers.

Questions	Answer Frequency
How much did you know about Buenos Aires barrios before visiting the site?	None at all (100%)
How much would you say you know now after exploring the site?	None at all (0%) A little (10%) Some (60%) A fair amount (20%) A lot (10%)
About how much time did you spend?	<10 min (50%) 10 min (40%) 30 min (10%)
How simple was it to navigate?	Difficult (0%) Challenging (10%) Neither difficult nor easy (20%) Some difficulty (40%) Easy (30%)
How effective were the graphics in providing information?	Not effective at all (0%) Not very effective (0%) Effective (10%) Fairly effective (50%) Very effective (40%)
How effective were the analytics descriptions in providing understanding?	Not effective at all (0%) Not very effective (0%) Effective (40%) Fairly effective (40%) Very effective (20%)
Does this inspire interest in the Buenos Aires housing market?	Yes (30%) No (20%) Maybe (50%)

Table 4. Results from the survey administered to users of the website.

8 DIVISION OF LABOR

Name	**Application Development**	**Application Text**	**Documentation**	**Deployment**	**Participant Recruitment**
Golder Kamuzora	✓	✓	✓		
Jacob Logas	✓		✓	✓	
Nora Mencinger	✓	✓			✓

Table 5. Visualization

Name	Collection	Cleaning	Management	Merging	Application Integration
Majid Ahmadi					
Zeynab Bahrami Bidoni	✓	✓		✓	
Golder Kamuzora		✓	✓	✓	✓
Breanna Lee	✓	✓		✓	
Jacob Logas	✓	✓	✓		✓
Nora Mencinger	✓	✓		✓	✓

Table 6. Data Tasks

Name	Price Gap	Buckhead Effect	Simple Statistics	Misclassification Correlation	Feature Selection	Application Integration
Majid Ahmadi	✓					
Zeynab Bahrami Bidoni		✓		✓		
Golder Kamuzora		✓	✓			✓
Breanna Lee					✓	
Jacob Logas		✓	✓		✓	✓
Nora Mencinger		✓	✓			✓

Table 7. Analysis

Name	Poster Design	Poster Visualizations	Poster Content	Report Visualizations	Report Content	Report Editing
Majid Ahmadi				✓	✓	
Zeynab Bahrami Bidoni		✓	✓	✓	✓	
Golder Kamuzora	✓	✓	✓	✓	✓	✓
Breanna Lee			✓			✓
Jacob Logas	✓	✓	✓	✓	✓	✓
Nora Mencinger	✓	✓	✓	✓	✓	✓

Table 8. Poster and Report

REFERENCES

[1] [n. d.]. Buenos Aires Ciudad - Gobierno de la Ciudad Autónoma de Buenos Aires |. https://www.buenosaires.gob.ar/

[2] [n. d.]. Buenos Aires: Uso del suelo y precio del metro cuadrado. http://www.properati.com.ar/p/new_iframes/parcelas/?

[3] [n. d.]. Properati Data. https://www.properati.com.ar/data

[4] [n. d.]. USD ARS Historical Data. https://www.investing.com/currencies/usd-ars-historical-data

[5] Aleph 0. [n. d.]. This project creates a map of the income distribution for Buenos Aires City usingo 2010 census, with RADIOS as areabreaks and using CAPECO and CONHAB indexes as proxy for income: alephcero/incomeM.. https://github.com/alephcero/incomeMapBuenosAires original-date: 2015-07-27T18:21:51Z.

[6] Sumit Agarwal, Souphala Chomsisengphet, and Olivier Hassler. [n. d.]. The impact of the 2001 financial crisis and the economic policy responses on the Argentine mortgage market. 14, 3 ([n. d.]), 242–270. https://doi.org/10.1016/j.jhe.2005.07.001

[7] Manuel Aristarán. [n. d.]. Ejercicio de visualización de los datos de recorridos de las bicicletas públicas de Buenos Aires: jazzido/vizbici. https://github.com/jazzido/vizbici original-date: 2013-05-11T19:36:59Z.

[8] Alejandro Baldominos, Iván Blanco, Antonio José Moreno, Rubén Iturrarte, Óscar Bernárdez, and Carlos Afonso. [n. d.]. Identifying Real Estate Opportunities using Machine Learning. 8, 11 ([n. d.]), 2321. https://doi.org/10.3390/app8112321 arXiv:1809.04933

[9] Jorge Blanco and Ricardo Apaolaza. [n. d.]. Socio-territorial inequality and differential mobility. Three key issues in the Buenos Aires Metropolitan Region. 67 ([n. d.]), 76–84. https://doi.org/10.1016/j.jtrangeo.2017.07.008

[10] Axel Borsdorf, Rodrigo Hildalgo, and Sonia Vidal-Koppmann. [n. d.]. Social segregation and gated communities in Santiago de Chile and Buenos Aires. A comparison. 54 ([n. d.]), 18–27. https://doi.org/10.1016/j.habitatint.2015.11.033

[11] Maximo Camacho, Marcos Dal Bianco, and Jaime Martinez-Martin. [n. d.]. Toward a more reliable picture of the economic activity: An application to Argentina. 132 ([n. d.]), 129–132. https://doi.org/10.1016/j.econlet.2015.03.032

[12] Paul Cheshire and Stephen Sheppard. [n. d.]. On the Price of Land and the Value of Amenities. 62, 246 ([n. d.]), 247. https://doi.org/10.2307/2554906

[13] Seong-Hoon Cho, Taeyoung Kim, Roland K. Roberts, Chad Hellwinckel, Seung Gyu Kim, and Brad Wilson. [n. d.]. Developing an amenity value calculator for urban forest landscapes. 43 ([n. d.]), 34–41. https://doi.org/10.1016/j.compenvurbsys.2013.10.005

[14] Marco De Nadai and Bruno Lepri. [n. d.]. The economic value of neighborhoods: Predicting real estate prices from the urban environment. ([n. d.]). arXiv:1808.02547 http://arxiv.org/abs/1808.02547

[15] Marco De Nadai, Radu Laurentiu Vieriu, Gloria Zen, Stefan Dragicevic, Nikhil Naik, Michele Caraviello, Cesar Augusto Hidalgo, Nicu Sebe, and Bruno Lepri. [n. d.]. Are Safer Looking Neighborhoods More Lively?: A Multimodal Investigation into Urban Life. In *Proceedings of the 2016 ACM on Multimedia Conference - MM '16* (2016). ACM Press, 1127–1135. https://doi.org/10.1145/2964284.2964312

[16] María Mercedes Di Virgilio. [n. d.]. Housing policy in Argentina: reflections on a decade of progressive social policy. 17, 2 ([n. d.]), 314–325. https://doi.org/10.1080/19491247.2016.1266868

[17] Yanjie Fu, Hui Xiong, Yong Ge, Yu Zheng, Zijun Yao, and Zhi-Hua Zhou. [n. d.]. Modeling of Geographic Dependencies for Real Estate Ranking. 11, 1 ([n. d.]), 1–27. https://doi.org/10.1145/2934692

[18] Erick Guerra, Camilo Caudillo, Cynthia Goytia, Tatiana Peralta Quiros, and Camila Rodriguez. [n. d.]. Residential location, urban form, and household transportation spending in Greater Buenos Aires. 72, 0 ([n. d.]). https://trid.trb.org/view/1540595

[19] Alexander Kraskov, Harald Stögbauer, and Peter Grassberger. [n. d.]. Estimating mutual information. 69, 6 ([n. d.]), 066138. https://doi.org/10.1103/PhysRevE.69.066138

[20] Lindsay Lehr. [n. d.]. HOUSING POLICY AND SOCIO-ECONOMIC RESIDENTIAL SEGREGATION: THE CASE OF BUENOS AIRES, ARGENTINA. https://repository.library.georgetown.edu/handle/10822/557553

[21] Han Li, Yehua Dennis Wei, Yangyi Wu, and Guang Tian. [n. d.]. Analyzing housing prices in Shanghai with open data: Amenity, accessibility and urban structure. ([n. d.]). https://doi.org/10.1016/j.cities.2018.11.016

[22] E. Muzzini, B.E. Puig, S. Anapolsky, T. Lonnberg, and V. Mora. 2016. *Leveraging the Potential of Argentine Cities: A Framework for Policy Action.* World Bank Publications. https://books.google.com/books?id=SK6fDQAAQBAJ

[23] María Carla Rodríguez and María Mercedes Di Virgilio. [n. d.]. A city for all? Public policy and resistance to gentrification in the southern neighborhoods of Buenos Aires. 37, 8 ([n. d.]), 1215–1234. https://doi.org/10.1080/02723638.2016.1152844

[24] Carolyn Thomas and Nicolás Cachanosky. [n. d.]. Argentina's post-2001 economy and the 2014 default. 60 ([n. d.]), 70–80. https://doi.org/10.1016/j.qref.2015.08.002

[25] Julie Wernau. [n. d.]. Argentina's Peso Plunges to Record Low. ([n. d.]). https://www.wsj.com/articles/argentinas-peso-plunges-to-record-low-1535578085

[26] Xiaoqing Eleanor Xu and Tao Chen. [n. d.]. The effect of monetary policy on real estate price growth in China. 20, 1 ([n. d.]), 62–77. https://doi.org/10.1016/j.pacfin.2011.08.001